



WATER LEVEL FORECASTING AND PREDICTION

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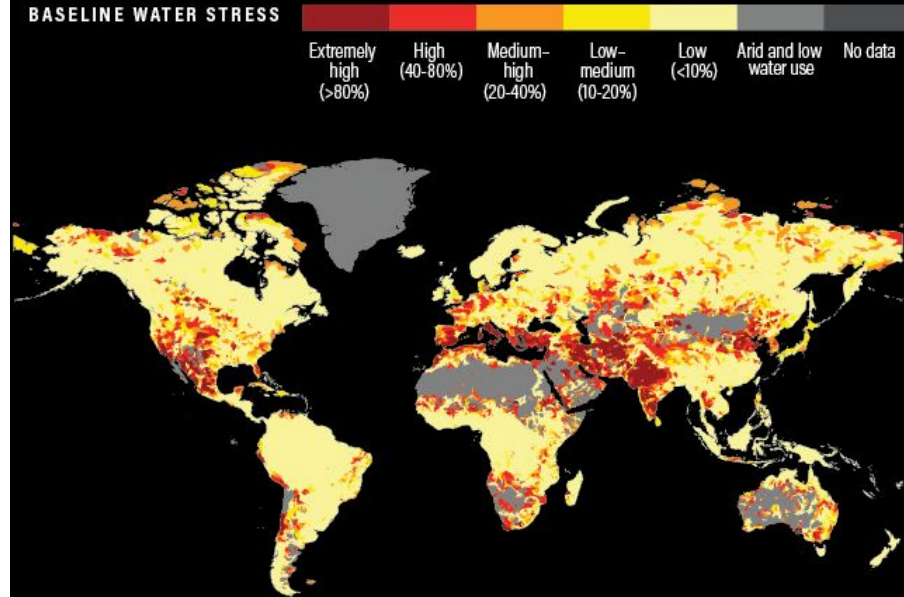
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REFERENCES

Introduction

- India - 13th among the world's 17 'extremely water-stressed' countries, - Aqueduct Water Risk Atlas by the World Resources Institute (WRI).
- "India is suffering from the worst water crisis in its history, and millions of lives and livelihoods are under threat." - NITI Aayog (2020)

17 COUNTRIES FACE EXTREMELY HIGH WATER STRESS



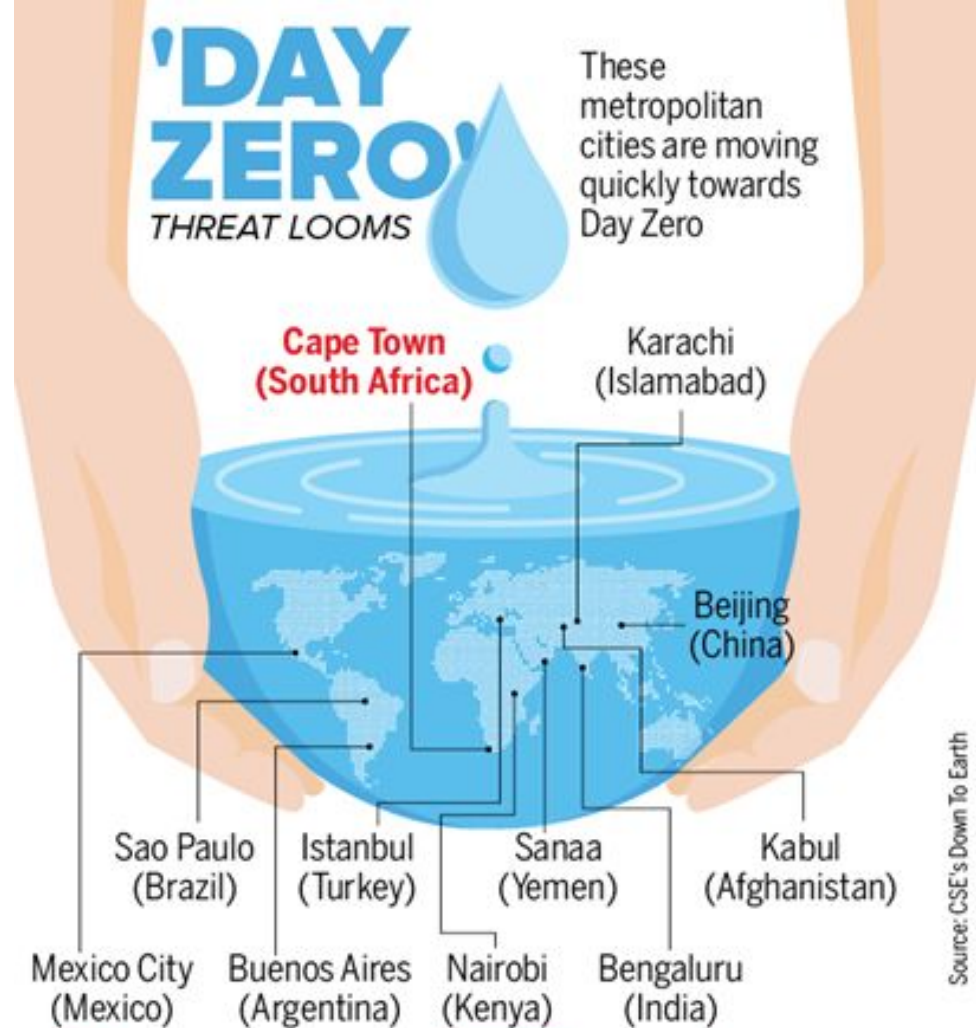
Source: wri.org/aqueduct

 **AQUEDUCT**

 **WORLD RESOURCES INSTITUTE**

Situation

- Cities in the Global South are facing unreliable, inadequate, and polluted supply of freshwater. - World Resources Report (WRI)
- These cities show that large urban population in the global south lack access to safe, reliable and affordable water.
- Almost half of all households in the studied cities still lack access to piped utility water.



BENGALURU COULD GO THE CAPE TOWN WAY

Waterbodies reduced by

79%

due to unplanned urbanisation and encroachment

Built-up area increases from

8% in 1973

to 77% now

Water table shrinks from 10-12 METRES to 76-91 METRES in just two decades

Number of extraction wells gone up from

5,000 to 4.5 LAKHS in 30 years

Bengaluru's population could reach

20.3 MILLION

by 2031 - and is growing by 3.5 per cent annually

City only uses

HALF



of its treatment capacity to treat waste and substantial amount is dumped into its waterbodies.

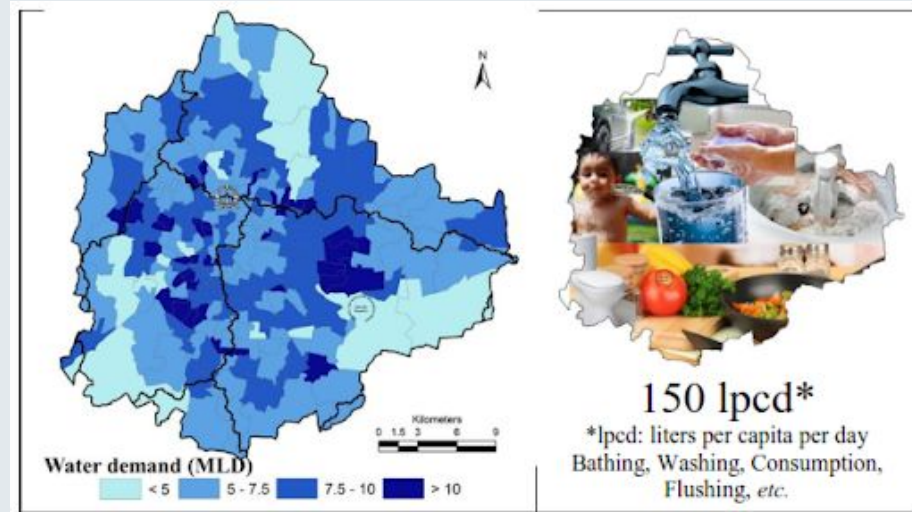
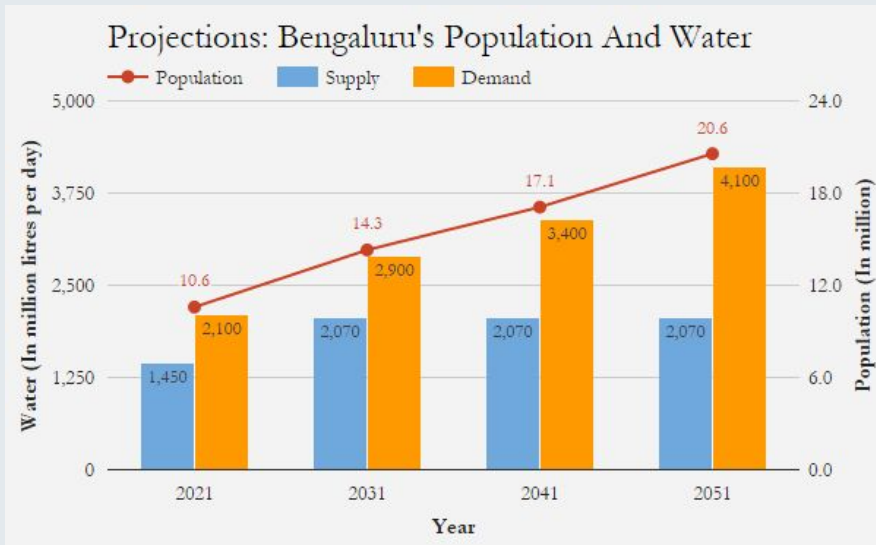
Bellandur Lake frothing due to toxic substances flowing into it through untreated sewage system from chemical factories and housing colonies around it.



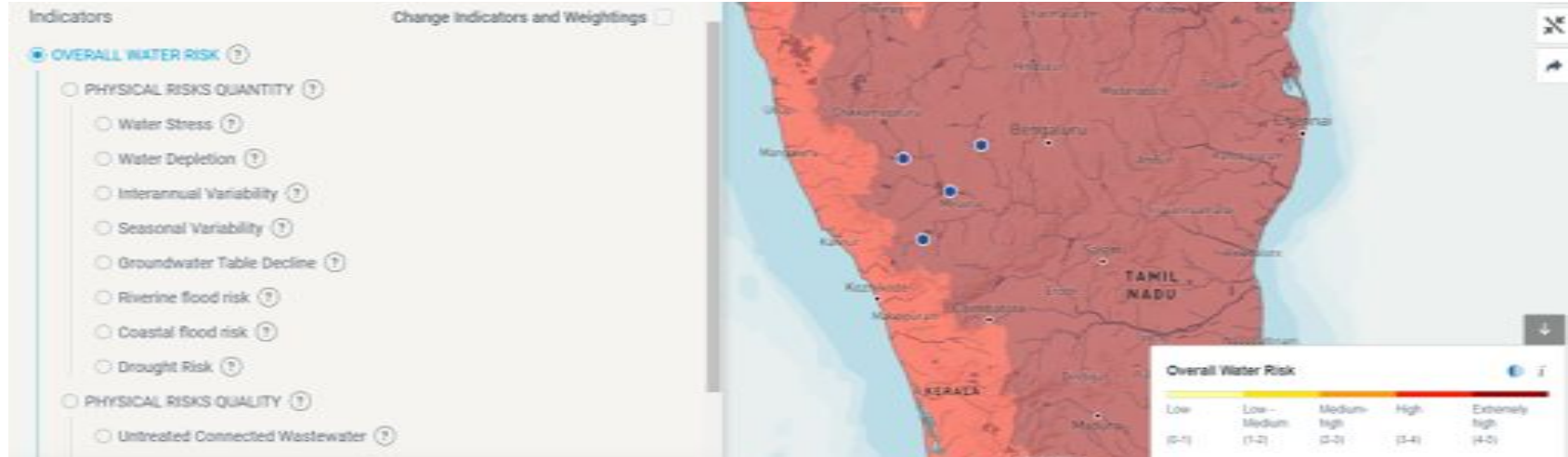
Case of BENGALURU

- On the verge of an imminent water crisis.
- Could follow Cape Town to become India's first city to run out of water

Bengaluru Water Demand Projection



Cauvery Water Basin Risk



Cauvery Water Basin Risk

CAUVERY BASIN

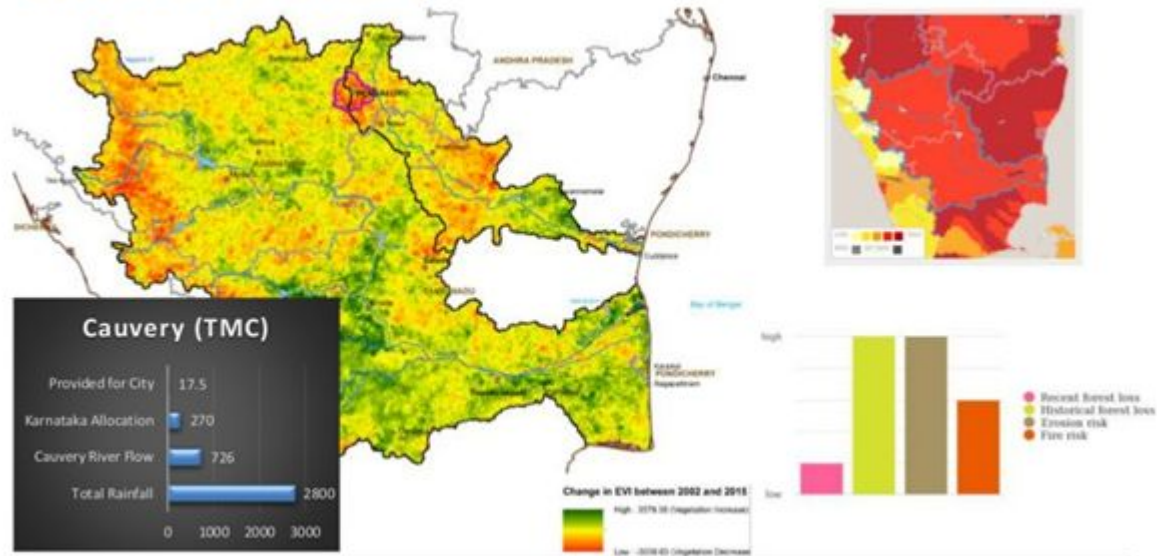


Image Source – GFW Water, Aqueduct

The **action** being
taken



Cities are investing in **larger and distant water sources**



Cities dig deeper to find water, but **extraction is much higher** than the rainfall can replenish.



What is the need of situation ?

- ✓ Transparent data to inform water supply risk management policymaking, especially during periods of water stress and increasing water insecurity in India.
- ✓ Access to near real-time water risk information as well as short-term forecasting (1-3 months in advance) of reservoir water availability.

**COMMUNITY'S WELL
BEING**

AQUATIC ECOSYSTEMS

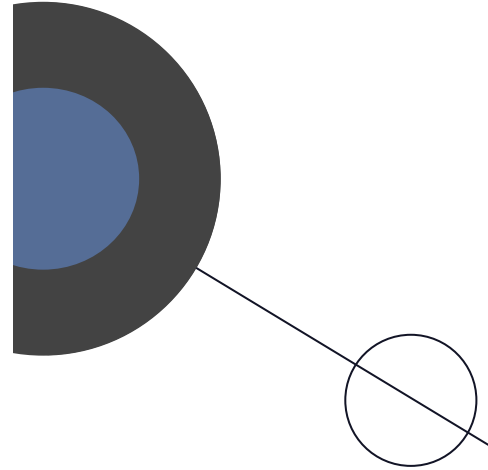
**Need for
water level
forecasting**

WATER INSECURITY

TRANSPARENT DATA

Objective

To build a time series analysis model using Deep Learning Techniques like Long Short Term Memory (LSTM), Convolutional Neural Networks (CNN), Facebook Prophet etc. with near real time reservoir level data for better temporal water level forecasting.



LITERATURE SURVEY



ANFIS

- **Adaptive network-based fuzzy inference system** uses a basic component of the type of fuzzy inference system (FIS) that projects input features to membership functions (MFs).
- Although, ANFIS gives good results, but there is no rigid rule in determining the number of MFs.



Artificial Neural Networks

- ANN has **potential in predicting groundwater level fluctuations** in an unsteady state of an aquifer influenced by pump and different weather conditions. (Coppola et al., Taiyuan et al.)
- **Good at simulating karstic and leaky aquifers** where other numerical models are weak in such cases.



Radial basis function networks

- RBFN is derived from the field of interpolation of multivariate functions, by using radial basic functions
- Unes et al. used RBFN model on daily historical water level data from 2006 to 2012
- The model could not discover non linear dynamics of dataset

LITERATURE SURVEY



Long Short Term Memory

- **Recurrent Neural Network (RNN)** capable of learning order dependence in **sequence prediction problems**.
(Yadav et al.)
- Applied to time series prediction which is a particularly hard problem to solve due to **the presence of long term trend, seasonal and cyclical fluctuations and random noise**.



Support Vector Machine (SVM)

- In **SVM**, an array of tasks is constructed as a rule integrates with planning and testing analysing data, including a few information events
- Khan et al. (2006) conducted a study to compare the performance of SVM and multilayer perceptron (MLP), using historical data from the year 1918 to 2001.
- SVM was able to predict the mean monthly lake water level successfully, up to 12 months in advance.



WHAT MACHINE LEARNING TECHNOLOGIES OUR PROJECT USES

XGBOOST

**LONG SHORT TERM
MEMORY**

**SUPPORT VECTOR
REGRESSION**

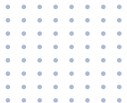
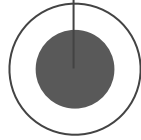
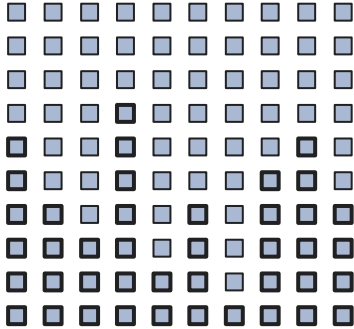


Tools / Technologies

- Python
- Pandas
- Google Colab
- Scikit Learn
- GeoJSON
- Plotly Dash
- TensorFlow
- Seaborn/ Matplotlib

FUNCTIONAL REQUIREMENTS

1. Dynamic Dashboard to view the results of the predictions
2. Visualizations of forecasted data
3. Predicting the water level using other features such as Inflow, Outflow, Rainfall, Soil Moisture, Humidity etc.
4. 1-3 months forecasts of water level
5. Correlation of the features crucial of water level prediction
6. Reservoir-wise forecasting
7. Scalable design to add new reservoir forecasting

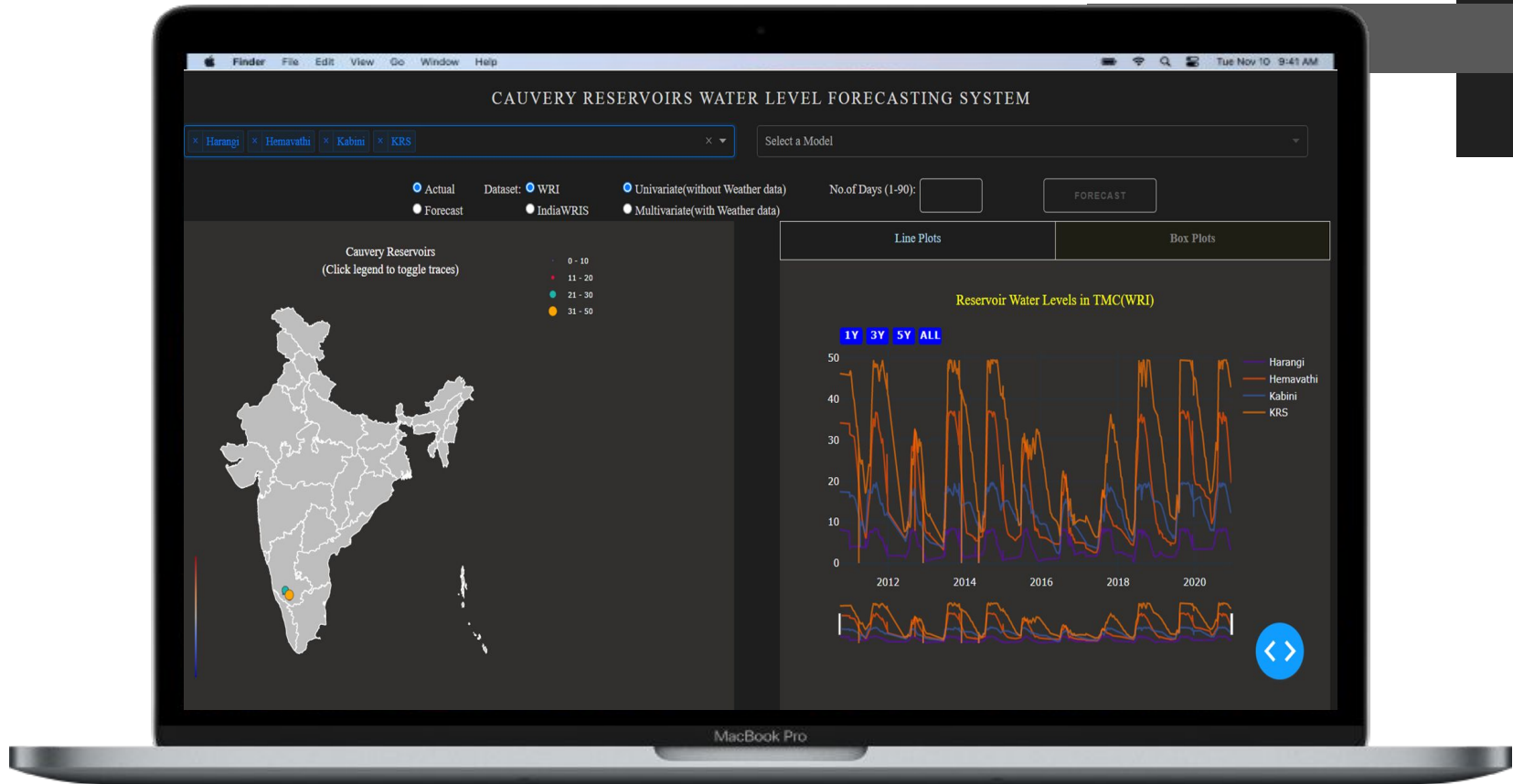


About the Datasets

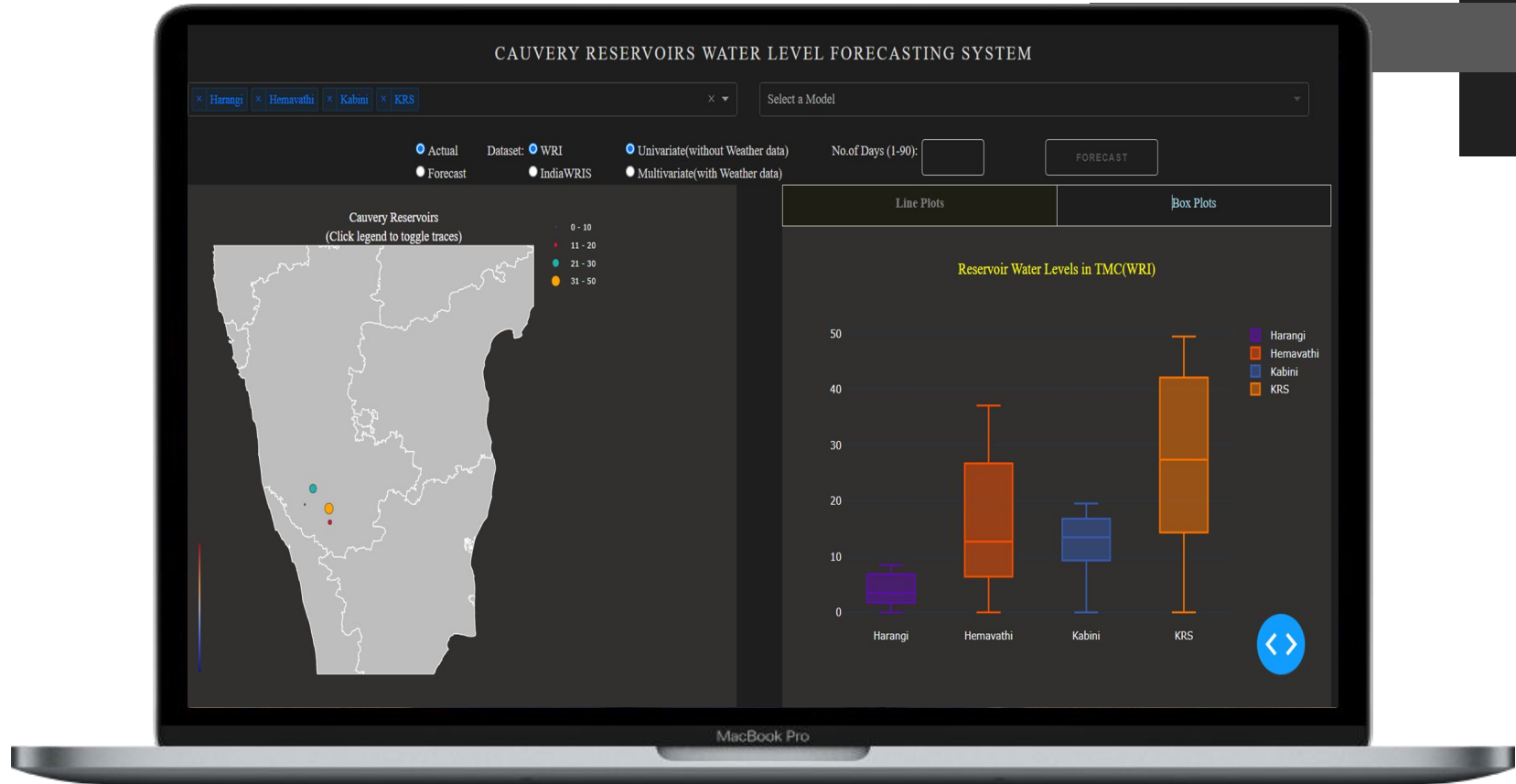
Dataset Source	Dataset Name	Date Range	Original Row Count	Missing Rows	Final Date Range	Final Row Count
WRI	<u>Harangi</u>	30-09-2010 to 16-12-2020	3321	332	01-01-2011 to 31-12-2020	3653
WRI	<u>Hemavathi</u>	30-09-2010 to 16-12-2020	3314	339	01-01-2011 to 31-12-2020	3653
WRI	KRS	30-09-2010 to 16-12-2020	3313	340	01-01-2011 to 31-12-2020	3653
WRI	<u>Kabini</u>	30-09-2010 to 16-12-2020	3314	339	01-01-2011 to 31-12-2020	3653

The dataset is obtained from the official WRI website and India WRIS datasets. It includes the geospatial data of four cauvery river basin reservoirs Hemavathi, Harangi, Kabini and KRS.

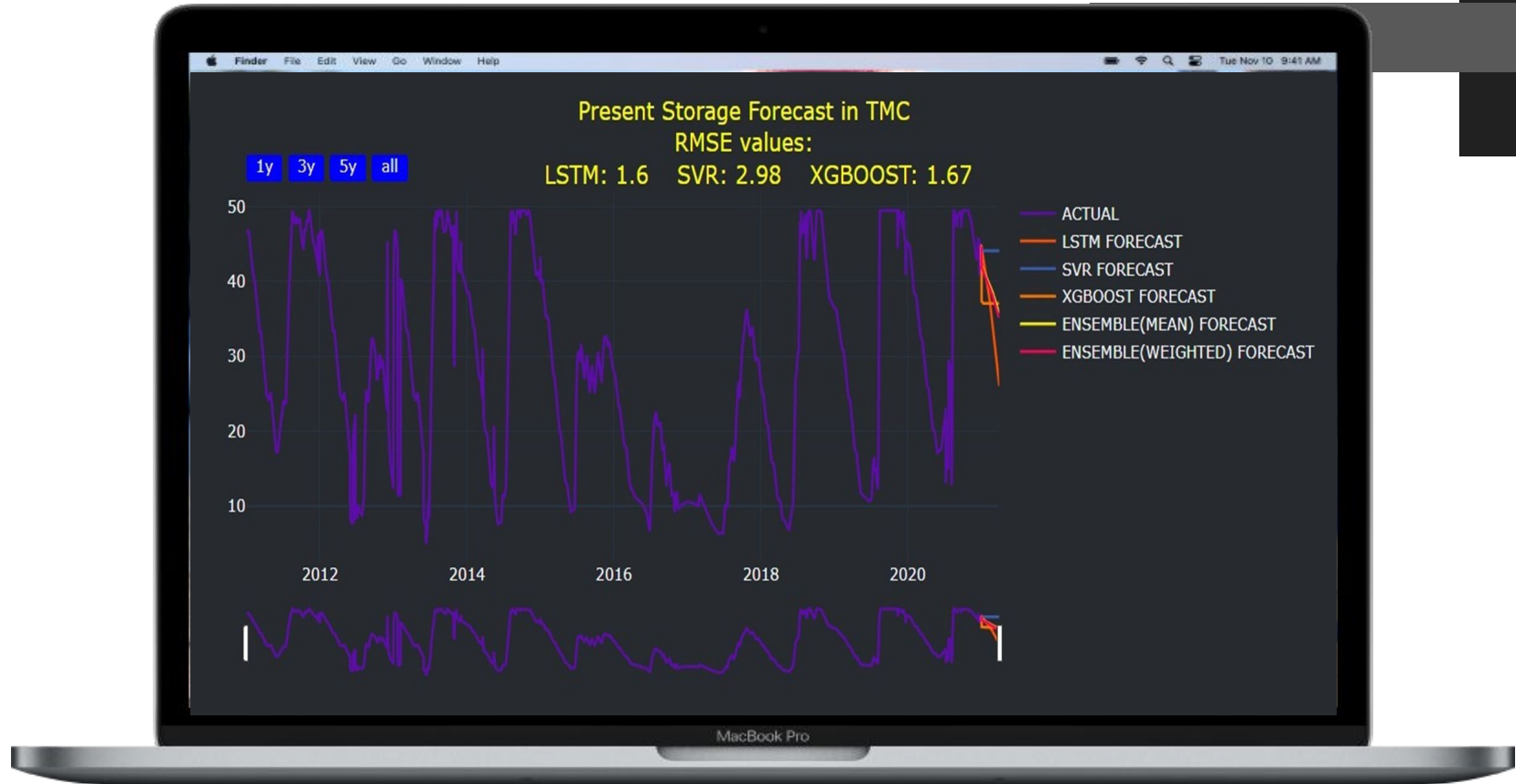
Final design of the project



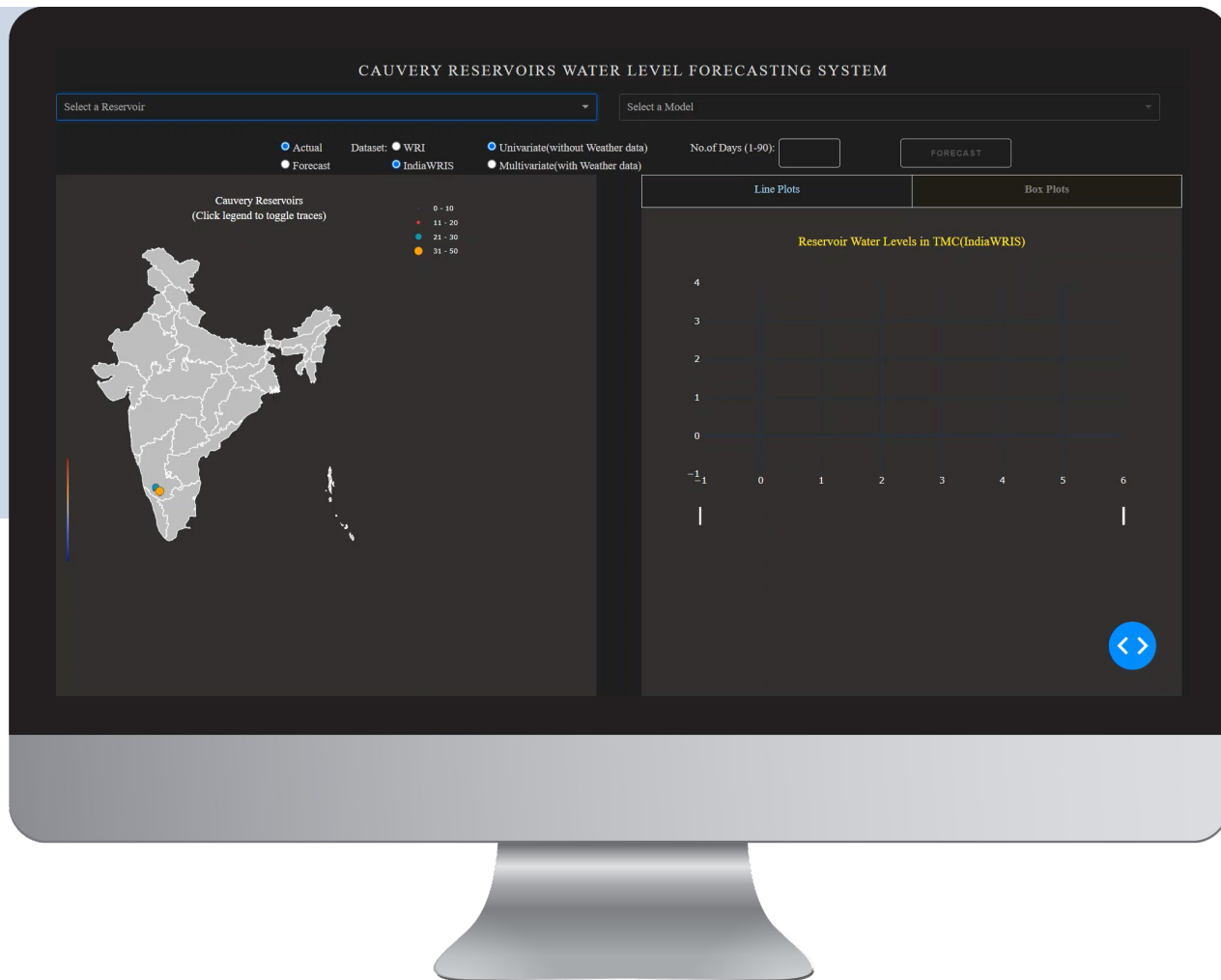
Final design of the project



Final design of the project



SNEAK
PEEK



REFERENCES

- [1] Evrendilek F, Karakaya N (2015) Spatiotemporal modeling of saturated dissolved oxygen through regressions after wavelet denoising of remotely and proximally sensed data. Earth Science Informatics 8: 247-254.
- [2] Lohani AK, Goel NK, Bhatia KKS (2014) Improving real time flood forecasting using fuzzy inference system. Journal of Hydrology 509: 25-41.
- [3] Firouzkouhi R (2011) Simulating groundwater resources of Aghili-Gotvand plain by using mathematical model of finite differences. Msd (Doctoral dissertation, Thesis, Shahid Chamran University of Ahwaz, Iran).
- [4] Lohani AA, Singh AK, Kasiviswanathan RDKS (2013) Radial Basis Artificial Neural Network Models and Comparative Performance. Journal of Indian Water Resources Society 33: 1-8.

REFERENCES

[5] Minns AW, Hall MJ (1996) Artificial neural networks as rainfall-runoff models. Hydrological sciences journal 41: 399-417.

[6] Coppola Jr E, Szidarovszky F, Poulton M, Charles E (2003) Artificial neural network approach for predicting transient water levels in a multilayered groundwater system under variable state, pumping, and climate conditions. Journal of Hydrologic Engineering 8: 348-360.

[7] Unaffordable and Undrinkable: Rethinking Urban Water Access in the Global South, ["https://www.wri.org/wri-citiesforall/publication/unaffordable-and-undrinkable-rethinking-urban-water-access-global-south"](https://www.wri.org/wri-citiesforall/publication/unaffordable-and-undrinkable-rethinking-urban-water-access-global-south) accessed on August 2021.

[8] Gronewold, Andrew & Clites, Anne & Hunter, Timothy & Stow, Craig. (2011). An appraisal of the Great Lakes advanced hydrologic prediction system. Lancet. 37. 577-583. 10.1016/j.jglr.2011.06.010.

REFERENCES

[9] Kimura, N.; Yoshinaga, I.; Sekijima, K.; Azechi, I.; Baba, D. Convolutional Neural Network Coupled with a Transfer-Learning Approach for Time-Series Flood Predictions. Water 2020, 12, 96.
<https://doi.org/10.3390/w12010096>

[10] Yadav, A.; Jha, K.; Sharan, A.; Optimizing LSTM for time series prediction in Indian stock market, Procedia Computer Science, Volume 167, 2020, Pages 2091-2100, ISSN 1877-0509,
<https://doi.org/10.1016/j.procs.2020.03.257>